Digging into Background Risk: Experiments with Farmers and Students

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Kenneth Arrow and John Pratt established principles for understanding risk and decision making that often directly inform experimental designs today (Arrow 1965; Pratt 1964). However, "real life" decisions involving risk are not as clearly defined as they are in this early economic theory, or the corresponding experiments. As argued by Ellsberg (1961), the risks associated with choices in the natural world are typically not as clearly defined due to uncertainties or risks that lie in the background of the decision. This background risk was recently explored by Harrison, List, and Towe (2007; hereafter HLT). Our paper continues to look at background risk and decision making by incorporating prior beliefs regarding ranges of payoffs into a theoretical model used to design a set of experiments.[1]

In addition to students, farmers were chosen as subjects for our experiments because of the inherent background risks faced in the agricultural industry. Although farmers are confronted with background risks that exist in other industries, such as price fluctuations from variability in consumer tastes, as well as input price and supply variability due to changing economic conditions, a farmer's production function depends heavily on weather conditions, adding a layer of background risk and a level of exposure that does not exist in many other industries.[2] The subpopulation of farmers is of interest because the added background risk present in the agricultural industry could lead to higher levels of risk tolerance than other subpopulations, either through sorting or experience over time. Alternatively, farmers may address background risk in a different manner than subjects more typically used in laboratory experiments, such as students. Understanding how risky choices are made in the "real world" is one interest of this current research, which attempts to bridge the gap between earlier laboratory work and the real world by evaluating alternate subpopulations through an appropriate experimental design (Andersen et al. 2010; List 2006).

Our experimental design elicits risk preferences through an instrument common to the literature: a multiple price list (see Andersen et al. 2006 for a discussion of this instrument). This experimental instrument has increased in popularity after its use by Charles Holt and Susan Laury and is often referred to informally as a "Holt–Laury" experiment (Holt and Laury 2002). Although this instrument has been fundamental in exploring risk preferences, it typically is used with known payoffs. In order to comment on background risk, HLT ran experiments with subjects at a coin show that included two framed versions of a Holt–Laury instrument using Morgan Silver Dollars as payoffs; one version included grades for the coins and one did not.

By including or withholding information about the grade of the coins, HLT varied the background risk that subjects faced. The results

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This article was presented in an invited paper session at the 2011 AAEA annual meeting in Pittsburg, PA. The articles in these sessions are not subjected to the journal's standard refereeing process.

[1] The farmer subjects were recruited through the Delta Institute, a partner in this research, and the American Farmland Trust.

[2] Irrigation and fertilization have mitigated background risk, but decisions still depend on weather. For example, excessive rain delayed the 2011 Illinois planting season. Also, although financial traders face related risk, farmers face direct exposure to their decisions.

Amer. J. Agr. Econ. 94(2): 457–463; doi: 10.1093/ajae/aar070

are intuitive but also very interesting: measures of risk aversion preferences for the Holt–Laury treatment were similar to the treatment that framed the original Holt–Laury experiment by using coins and included each coin's grade, while subjects displayed much more risk aversion toward the framed but ungraded treatment.[3] In short, there is suggestive evidence that the type of background risk that pervades decision making in the field is likely to lead to higher levels of risk aversion than the estimates elicited in the lab.

Our work extends the previous research by designing an experimental instrument for background risk that we hope can be used for a broad group of subjects. In the spirit of HLT, the standard Holt–Laury is modified in this experimental design by replacing monetary values with images of bags of quarters in place of Morgan Silver dollars and weights of the bags of quarters in place of a grading. Also, in order to incorporate a measure of a subject's prior beliefs concerning the distribution of payoffs, our experimental design includes two additional instruments to those run in HLT: one instrument to elicit a subject's prior beliefs and one multiple price list that directly states a payoff range.

This work is the first stage in research on how risk may affect a farmer's decision to enroll in carbon trading markets. In addition to the background risks that farmers face in their chosen profession, the decision to utilize a carbon market is fraught with background risk, such as the expected price of carbon and the need to satisfy requirements of the trading board, such as multiple-year carbon sequestration. The results reported here are inconclusive but are suggestive that farmers are more risk averse than students. Further, there is some evidence that our bags-of-coins instrument affects risk preferences similarly to HLT. The results will be used to inform an experimental design to be conducted in the latter half of 2011 and the early part of 2012.

This work contributes to the current literature on risk by providing a formalization of the background risk that may exist in real-life decisions. By exploring background risk through subjects' prior beliefs on underlying distributions, it also adds an experimental analysis to the growing literature on ambiguous payoffs. Further, this work takes steps toward bridging the gap between laboratory results concerning risk and real world decisions by augmenting an experimental instrument and comparing two different subpopulations. The next section briefly reviews the extensive literature on risk, ambiguity, and background risk. It is followed by an introduction to the theoretical model, the experimental design, and a presentation of the results.

Literature

The development of the Arrow–Pratt index of risk aversion allowed for the advancement of research on many aspects of decision making, including asset valuation, contracts, and insurance (Arrow 1965; Pratt 1964). Economists have tried to isolate this index both in the laboratory and in the field (Binswanger 1980; Harrison and Rutstrom 2008). The Holt–Laury experimental instrument has been used frequently in both laboratory and field experiments due to its transparency and simplicity in calculating the risk aversion coefficient. We choose to utilize this method of elicitation to keep with the convention of the existing literature.

The Holt–Laury instrument's use can extend beyond eliciting risk preferences to investigate concepts closely related to risk, such as background risk. The efforts to provide empirical support for background risk are sparse but evidence for a directly related topic introduced by Gollier (1996), "risk vulnerability," was found in the paper by Lee (2008): subjects were found to be more risk averse after the introduction of background risk. The experiments reported by Lee (2008) also show that subjects exhibit decreasing absolute risk aversion, as suggested in the theory set forth by Gollier (1996). As discussed above, an empirical example of background risk is HLT, which provides experimental evidence that the introduction of background risk may cause a subject to become more risk averse.

Rather than affecting risk preferences directly, background risk may reflect an aversion or uncertainty due to the ambiguity surrounding the risky decision. For example, in HLT, once the grades of the coins were taken away, subjects were no longer certain about the value of the coin and unable to make a precise

[3] The results predict mean constant relative risk aversion parameters of 0.88, 0.76, and 4.78 for the Holt–Laury, graded coin, and ungraded coin treatments, respectively. The authors also test prospect theory as an alternative to an expected utility model and find that the impact of ungraded coins remains positive and significant but reduces substantially: from 3.974 to 0.59.

calculation in order to make a decision. The relationship between ambiguity and risk aversion has been documented at least since Savage (1972) made the distinction between risk as the subject knowing the probability distributions, and ambiguity as not knowing the probabilities associated with the choices.

Savage's *subjective expected utility* representation of preferences was one of the original models for risk and ambiguity. However, the experiments of Ellsberg (1961) exposed technical issues, which gave rise to more general versions of the model, including prospect theory (see Camerer and Weber 1992 for a discussion).[4] Our research leaves open the possibility of incorporating these models but focuses on the impact of a subject's prior belief for a payoff range, generated through background risk, on risk preferences.

Theory and Experimental Design

Our theoretical model is formulated under an assumption of constant relative risk aversion (CRRA) and thus assumes the following utility model: $u(x) = \frac{x^{(1-r)}}{(1-r)}$. The parameter of interest is the CRRA preference parameter, represented by r. The CRRA parameter can be identified by using the standard Holt–Laury instrument, which presents subjects with decisions over two lotteries, lottery A and lottery B. Each lottery has the same probability assigned to two payoffs, but the payoffs differ in amount. Under CRRA, the expected utility for a lottery with two possible payoffs, x_1 and x_2, and a probability for each payoff, p_1 and $p_2 = (1 - p_1)$, is:

$$(1) \qquad E(u(x)) = p_1 \frac{x_1^{(1-r)}}{(1-r)} + (1-p_1)\frac{x_2^{(1-r)}}{(1-r)}$$

A Holt–Laury experimental design identifies r through the decision at which subjects switch between the less risky lottery (typically lottery A) and the more risky lottery (typically lottery B). The switch bounds a subject's r between the CRRA values that would make the decisions equivalent in expected value.

In order to consider the change in CRRA values when background risk is introduced, we take a step back and investigate how a subject's prior beliefs concerning the value of the now uncertain payoff relate to background risk and formulate an expected utility model that incorporates background risk as a weighting of an ambiguous payoff. That is, when subjects are given a set of ranges, $x_{1,L}$ to $x_{1,H}$ and $x_{1,L}$ to $x_{1,H}$, rather than a set of known payoffs, x_1 and x_2, we specify the expected utility for each choice as:

$$(2) \qquad E(u(x)) = p_1 \frac{(\alpha x_{1,L} + (1-\alpha)x_{1,H})^{(1-r)}}{(1-r)} + (1-p_1)\frac{(\alpha x_{2,L} + (1-\alpha)x_{2,H})^{(1-r)}}{(1-r)}$$

where α is an agent's prior placed on payoff ranges. This formulation assumes that subjects first act upon priors and form an expected value of a payoff range based on α: $E(x_k) = \alpha x_{k,L} + (1-\alpha)x_{k,H}$.[5] The adjusted theory suggests including two new experiments in addition to those run in HLT: one experiment to uncover α without r and one experiment that includes unframed background risk to jointly uncover r and α.

Our experimental design consists of four treatments that use multiple price lists: Holt–Laury (HL), Holt–Laury with Range (HLR), Background Risk (BR), and Background Risk with Information (BRI). There are two main differences between the price lists used: the way payoffs are presented, either as stated values or pictures of bags of coins, and the amount of ambiguity in the payoff amount, either by including or excluding a range in the case of HL and HLR or by including or excluding the weight of the bags of coins in the case of BR and BRI.[6] Examples of decision rows from the instruments can be found in figure 1. Images of the bags of coins are found in figure 2.[7] We evaluate the differences in responses between HL and HLR andbetween BR and BRI using primarily a within design. In addition, an instrument that elicits a subject's prior for a payoff range is administered with HL and HLR, in order to explore the above theory.

[4] Ellsberg (1961) exposed the problem that subjects do not always assign probabilities in a consistent manner. That is, subjects who are presented with choices of events, with known and unknown probabilities, may not act in concert with an assumption that one probability was assigned to each unknown event, if the groupings of events change.

[5] We also assume α is consistent across ranges over reasonably similar payoffs.

[6] The range was generated from averages of a separate student activity in which students submitted high- and low-end guesses of the number of quarters in each bag.

[7] The amount of quarters ranged from five to forty. The quarters were stacked to intentionally obfuscate the amount of quarters in each bag.

Option A	Option B	Decision
Holt and Laury (HL)		
50% for $5.75, 50% for $3.50	50% for $10, 50% for $1.25	A B
60% for $5.75, 40% for $3.50	60% for $10, 40% for $1.25	A B
Holt and Laury with Range (HLR)		
10% for a value between $3.75 and $6.75 90% for a value between $2.50 and $4.75	10% for a value between $7 and $14 90% for a value between $0.50 and $2	A B
20% for a value between $3.75 and $6.75 80% for a value between $2.50 and $4.75	20% for a value between $7 and $14 80% for a value between $0.50 and $2	A B
Background Risk (BR) and Background Risk with Information (BRI)		
70% for BAG A, 30% for BAG B	70% for BAG C, 30% for BAG D	A B
80% for BAG A, 20% for BAG B	80% for BAG C, 20% for BAG D	A B

Figure 1. Multiple price lists: stated value and bags of coins

Two example rows from each instrument that consisted of ten rows each. The rows started with 10% and 90% and increased to 100% and 0%, which is standard format for Holt–Laury multiple price list instruments.

In order to elicit the priors of the subjects, we employ a method similar to but different than instruments used in research on ambiguity. Research on ambiguity typically asks subjects to choose between a lottery with an outcome of unknown probability and a lottery with known probabilities (Gazzale et al. 2009). However, we do not utilize lotteries but only a certain payoff and an unknown range because our interest in this experiment is to uncover priors rather than subjects' tastes for ambiguity. In our experiment the ambiguous range was $1 to $10, while the certain value increased incrementally from $1 to $10. Examples of the decision rows for the prior instrument are given in figure 3.

For our main analysis, subjects received either HLR and HL or BR and BRI. Each subject received the instrument with more ambiguous payoffs first (BR or HLR).[8] Subjects would then receive either an ambiguity treatment or an unrelated question regarding charitable donations. The question regarding charities created separation in the decision making with the intent of avoiding subjects automatically repeating previous choices. The final instrument was the remaining price list with less ambiguous payoffs, either BRI or HL.

Two populations of subjects were recruited: farmers and students. There were two sessions with farmers: one located at the Soil and Water Conservation District Office in Dekalb, Illinois, and one at an agricultural conference in Springfield, Illinois. The two sessions took place one week apart and received different sets of treatments. Twenty-five participants at Dekalb were

[8] The instruments were presented in this order so that subjects would not receive information in earlier instruments that would inform decisions in later instruments. Two sessions were run in the reverse order, with the instruments with more information, BRI and HL, first. The only significant difference was the HL CRRA estimate. Due to the limited sample size recruited, farmers did not receive treatments in the reverse order.

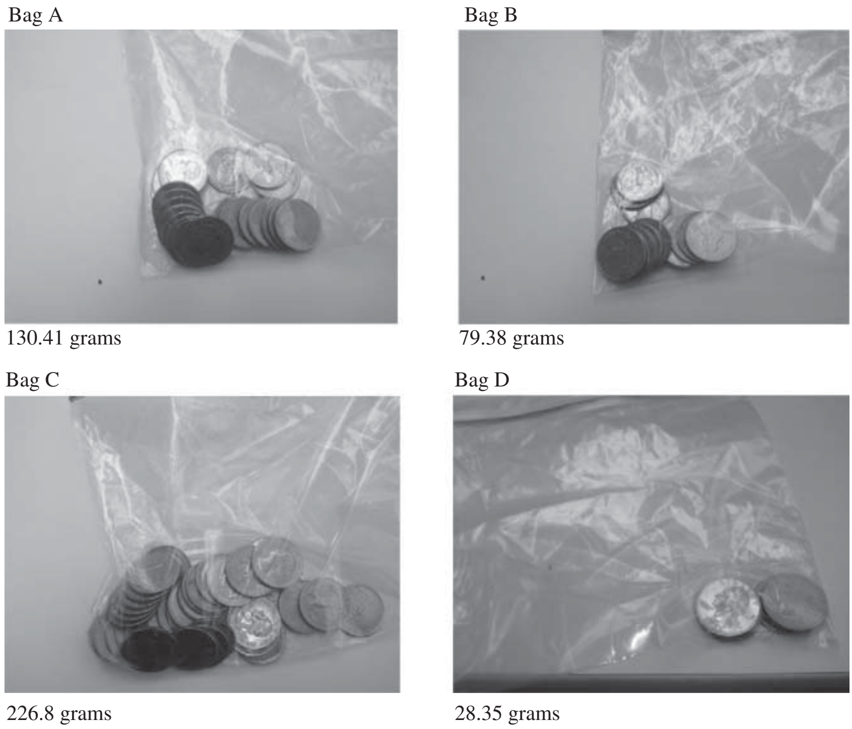

Figure 2. Images of bags of quarters (with weights)

Each bag of quarters corresponded to an outcome in the multiple price lists of the BR and BRI treatments. Weights were provided for only the BRI treatment.

	Option A	Option B	Decision
1	$1.00	A value between $0.00 and $10.00	A B
2	$2.00	A value between $0.00 and $10.00	A B
3	$3.00	A value between $0.00 and $10.00	A B
4	$4.00	A value between $0.00 and $10.00	A B
5	$5.00	A value between $0.00 and $10.00	A B
6	$6.00	A value between $0.00 and $10.00	A B
7	$7.00	A value between $0.00 and $10.00	A B
8	$8.00	A value between $0.00 and $10.00	A B
9	$9.00	A value between $0.00 and $10.00	A B
10	$10.00	A value between $0.00 and $10.00	A B

Figure 3. Experimental instrument for eliciting prior for payoff range

presented with the instruments utilizing bags of coins (BR and BRI) and sixteen participants at Springfield received the instruments stating monetary values (HL and HLR).

Student subjects enrolled in economics classes at the University of Chicago and were also recruited to participate and were separated into four sessions. For these subjects,

Table 1. Average Risk Aversion (midpoint)

Subject Population	Holt–Laury	Holt–Laury with Range	Background Risk with Information	Background Risk
Farmers	**0.389**	**0.623**	**0.525**	**0.736**
Standard deviation	(0.212)	(0.565)	(0.652)	(0.608)
Observations	*8*	*8*	*21*	*19*
Students	**0.180**	**0.483**	**0.499**	**0.600**
Standard deviation	(0.424)	(0.519)	(0.374)	(0.337)
Observations	*11*	*12*	*13*	*13*
All	**0.268**	**0.539**	**0.515**	**0.680**
Standard deviation	(0.358)	(0.528)	(0.556)	(0.513)
Observations	*19*	*20*	*34*	*32*

Note: Means calculated from midpoint of risk aversion for the decisions that each subject switched between. Subjects with inconsistent preferences (switched decision columns more than once) and without a quantifiable midpoint (did not switch) were not included. For students, 3 HL and 2 HLR responses were removed. For farmers, 8 HL, 6 HLR, 6 BR, and 3 BRI were removed.

payment was in the form of raffle tickets for a free dinner with two economics professors.[9] Two sessions of students received the same treatments as did the farmers, while two other sessions received the treatments in reverse order.[10]

Results

Table 1 presents CRRA values calculated from the midpoint of the range of CRRA values given for the decision rows that an agent switched from option A to option B.[11] The averages in table 1 show that our results are in line with previous research when using the standard Holt–Laury instrument: subjects are on average slightly risk averse (Andersen et al. 2006; Harrison and Rutstrom 2008; Holt and Laury 2002). However, farmers tended to switch later than students and thus could be classified as slightly more risk averse, 0.389 versus 0.180, but the difference is not statistically significant (Wilcoxon rank-sum test). This difference remains when a range is used rather than known payoffs, 0.623 versus 0.483, but it remains insignificant.

The bags of coins were intended to replicate the results from the framed treatments of HLT, which found drastic differences between their graded and ungraded coins (CRRAs of 0.76 and 4.78 for the graded and ungraded coins, respectively). Looking at table 1 we see that the CRRA values for farmers and students are similar across samples, 0.525 and 0.499, and 0.736 and 0.600, respectively, and have a similar increase across treatments BRI and BR, with none of the comparisons being significantly different using appropriate tests. This suggests that the background risk caused by the instrument does not have a large impact on the subjects' decisions. Further, although there is a substantial increase in the magnitude of the CRRA value between HL and HLR for students, it is not significantly different.

It is possible that the current results are affected by the within design. In order to test this, the sample was restricted to the first round of the two sessions with students designed to mirror the sessions with farmers and the first round of the two sessions with students that reversed the order of the treatments (not reported in table 1). This restricted sample provided a between test of each treatment. Although the mean CRRA estimate of treatments HL and BR, 0.158 (SD = 0.451, $n = 17$) and 0.6 (SD = 0.337, $n = 13$), respectively, are significantly different, the difference between the mean from either treatment and the mean CRRA from BRI, 0.4 (SD = 0.435, $n = 13$), is not.[12] This provides evidence that using images of coins affects risk preferences but providing weights does not.[13]

Incorporating the priors we elicited from subjects on the values reported in table 1 does not significantly affect the results. This is found by first estimating the priors by recording when a subject switched from option A (a certain

[9] Students at the University of Chicago hold both professors in high regard.

[10] Instructions can be obtained from the authors and are similar to those of Harrison et al. (2007).

[11] An agent with a CRRA value less than 0 is considered risk loving; equal to 0 is considered risk neutral; and greater than 0 is considered risk averse.

[12] The p-values from rank-sum tests are as follows: HL and BR, $p = .0041$, BR and BRI, $p = .1244$ and HL and BR, $p = .1032$.

[13] Other evidence of the within-design's effect is found in four student sessions run as a between-design. These sessions resulted in the following CRRA values: BRI: 0.165 and BR: 0.558, which are significantly different at the 5% level (Wilcoxon rank-sum test).

payoff) to option B (a payoff range). The midpoint of the decision between which agents switch is used to calculate the values. That is, if the subject switched between \$4 and \$5, the estimated prior, α, would be 0.45. Using this measure, the mean prior estimate for farmers was 0.41 (SD = 0.20, $n = 9$) and for students 0.47 (SD = 0.09, $n = 12$).[14] Using the subjects' individual priors to calculate the perceived payoff increases, the estimated CRRA goes to 0.79 for farmers and to 0.78 for students in the BRI treatment.

Conclusions

This paper moves toward a goal of understanding how risk preferences and other factors influence a farmer's decision to participate in a carbon offset market. In order to approach this goal, we explored an important question being considered in current research: How should experimental results from laboratory sessions be applied to the field or real world settings? (Andersen et al. 2010; Levitt and List 2007; List 2006; Reynaud and Couture 2010). We explored the gap between the lab and the real world by including background risk in a laboratory setting and drawing subjects from both a standard student population and a nonstandard farmer population.

The results suggest that our experimental design could be used to understand the impact of background risk on risk preferences if a between design were used. Further, there is suggestive evidence that farmers are slightly more risk averse than students. This is interesting considering the inherent risk in the agricultural industry. The lower risk tolerance exhibited by farmers could be due to the abstract nature of the experimental instruments, which students may be more familiar with. This alternative hypothesis is left to be considered in future experiments.

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[14] As with the risk elicitation, the sample excludes those with inconsistent responses.